Applying the Construction-Integration Framework to Aesthetic Responses to Representational Artworks

Keith Millis
Northern Illinois University

Meredith Larson
Northwestern University

Send all correspondence to:
Keith Millis
Department of Psychology
Northern Illinois University
Dekalb, IL 60115, USA
e-mail: kmillis@niu.edu
phone: 815-763-7087
ABSTRACT

Kintsch’s (1988) construction-integration (CI) framework was applied to aesthetic responses to artwork. Art novices in three studies viewed and rated representational artworks on aesthetic responses, including enjoyment, number of experienced thoughts, and achieved understanding. Parameters based on the CI framework as well as variables assessing surface representation were computed for each artwork and were entered in multiple regression equations predicting the ratings. In study 1, the number of activated concepts, a measure of construction, and the average activation level of the concepts, a measure of integration, predicted the aesthetic ratings. In study 2, the number of concepts predicted the ratings in a brief viewing time condition but not in a long viewing time condition, when construction would have been completed. In that study, the activation level of the concepts predicted the ratings in both brief and long viewing time conditions. In study 3, the CI framework predicted emotional but not cognitive-based responses. The results and the CI framework are discussed in the context of models of aesthetic processing.

Key Terms:

construction-integration
experimental aesthetics
concept activation
discourse processing
Applying the Construction-Integration Framework to Aesthetic Responses to Representational Artworks

The Construction-Integration framework developed by Walter Kintsch (1988; 1998) has been very popular among psychologists in accounting for experimental findings across a number of domains (e.g., see Weaver & Mannes, 1995). Although it was developed in the context of language comprehension, it has been applied to learning from hypertext (Shapiro, 1998), planning (Mannes & Kintsch, 1992), skill acquisition (Doane, McNamara, Kintsch, Polson, & Clawson, 1992), reasoning (Arocha & Patel, 1995), and impression formation (Kintsch, 1998). According to the framework, comprehension proceeds across cycles of encoding the material (e.g., sentence clauses). Each cycle consists of a construction phase in which newly encoded concepts and close associates from long-term memory are activated in working memory in an automatic and bottom-up fashion. The representation then undergoes an integration process where inappropriate concepts are deactivated and pruned, simplifying the representation and making it coherent. During the integration phase, the comprehender might add knowledge-based inferences to the representation.

The goal of this paper is to examine whether the CI framework can account for some aesthetic responses to viewing representational paintings and artworks. Representational artworks depict recognizable objects (we did not attempt to examine abstract artwork). Aesthetic responses refer to the set of cognitive processes and emotional responses that occur as the perceiver attempts to classify and understand an artwork (Berlyne, 1971; Leder, Belke, Oeberst & Augustin, 2004). Aesthetic responses include a number of intertwined cognitive and emotional processes regarding the artwork, including classification, perceptual analyses, memory retrieval,
interpreting and evaluating the artwork (Leder et al., 2004). Not all of these processes would be implicated for all viewers and for all artworks, however. We examined art novices who viewed illustrations which were introduced as art. They would not be expected to arrive at aesthetic judgments in the manner as more experienced viewers. For example, novice viewers emphasize a pleasure-based reception to art whereas experts emphasize a cognitive-based reception (Cupchik & Laszlo, 1992). Therefore, when we refer to aesthetic responses, we are referring to the (primarily) emotional by-products of processes that novices conduct as they visually inspect representational art.

The CI framework might be useful for understanding aesthetic responses because there are several similarities that exist between discourse, a domain in which the CI framework has been successfully applied, and artwork. Both text and artwork involve pragmatic agents: the artist and writer both create, and the viewer and reader both comprehend. Sometimes both media depict protagonists and antagonists. Writers and artists employ particular devices to create aesthetic experiences. Writers will order words in a sentence or the events in a story to create a particular effect in the reader, such as surprise or suspense (Brewer & Lichtenstein, 1982). Artists will compose their art using certain devices, such as perspective or balance in order to achieve similar effects. Stories often contain a theme, and often a unifying theme can bring coherence to diverse elements in an artwork (Graesser, Person & Johnston, 1996). Moreover, in order to understand text and art, the reader and viewer will make knowledge-based inferences about the material. Lastly, the comprehension process proceeds across time, as the comprehender encodes the next clause in written discourse or the next visual element in an artwork.

Another similarity between comprehending art and text is that both involve the
construction of similar levels of representation. Readers (and listeners) construct at least three levels of representation during the comprehension of text: surface, textbase, and situation model (Graesser, Millis & Zwaan, 1997; van Dijk & Kintsch, 1983). The surface representation preserves exact wording, syntax, and font information. The textbase represents the propositional structure of the text. The situation model depicts the events depicted in text, and contains information from the text combined with the reader’s world knowledge about protagonists, time, space, causality, and intentionality (Zwaan, Langston, & Graesser, 1995). Similarly, Solso (1994, 2003) has argued that viewers of art construct three levels of representation that closely correspond to the above three levels. He refers to them as level 1, 2, and 3. Solso’s “Level 1” representation contains the colors, shading, and the contours of the artwork. There is no meaning in the conventional sense at this level, even if there are recognizable objects depicted. This representation preserves the surface information of the artwork. The “Level 2” representation contains the concepts explicitly shown in the artwork and recognized by the viewer. In the case of representational art, this would consist of the concepts that are depicted. In the case of abstract art, this level would include recognizable shapes (e.g., blue triangle). Because this level is analogous to the textbase, we refer to it as the artbase representation. The “Level 3” representation contains inferences about the artwork and interpretation(s) made by the viewer. This is most analogous to the situation model. According to Solso, we can also experience deep emotional connections to the artwork that approaches the mystical and ineffable. This level is “being ‘at one’ with the art; it is commingling a painting with universal properties of the mind; it is seeing one’s primal mind in a painting” (Solso, 2003, p. 258).

As an example of the three levels, consider the artwork in Figure 1. The colors, contours,
and shading would reside at the surface (Level 1) representation. The artbase (Level 2) representation would include the concepts of maid, carrying, sheets, staircase, portrait, etc. and the propositions in which they are embedded (e.g., CARRY (MAID, SHEETS), WALKING-ON (MAID, STAIRS) etc.). The Level 3 representation might contain inferences regarding the emotional state of the maid, the portrait hanging on the wall, social class, historical and spatial inferences, aesthetic judgments regarding composition, and the goal of the artist. Whereas Solso’s analysis provides a link between models of text discourse to art comprehension on the types of representations that are generated, it does not describe the process of constructing the different representations and the possible links between them and various aesthetic emotions.

The goal of this study is to examine whether the CI framework can by used to describe the artbase representation and whether that process is correlated with aesthetic responses.

*Applying CI to Aesthetic Responses*

In applying the CI framework to viewing artwork, it is reasonable to assume that recognized objects portrayed in the explicit artwork (along with the title if encoded) would automatically generate a representation corresponding to the construction phase. It would consist of the explicit concepts activated by the images and words and close associates in semantic memory. This initial representation could be fragmented or incoherent to the extent that concepts which would normally not be activated together are done so concurrently. After construction, the viewer would simplify and reorganize the representation in an effort to achieve coherence. This would consist of integration. During this phase, the viewer would also generate inferences about the scene(s) the artwork depicts. The construction and integration cycle as the viewer spans the artwork, encoding the different elements.
Admittedly, it is unclear whether existing data in cognitive psychology or in experimental aesthetics can support or refute a CI account of aesthetic processing. One reason is that few studies have explicitly or implicitly addressed the processes implicated in the CI framework. One might be Millis (2001) who reported that artworks paired with metaphoric titles were enjoyed more than artworks paired with a title that described the scene, a random title, or artworks without a title. The finding suggests pleasure arises from constructing an elaborated and coherent representation of the artwork, a process that occurs during integration. The title effect occurred even when participants were told to ignore the titles because they were contrived. This result suggested the concepts leading to integration were automatically activated, an assumption of the construction phase. In addition, Leder, Carbon and Ripsas (2006) found that descriptive titles increased understanding for abstract paintings under very brief presentation times (1 s), whereas elaborative titles increased understanding under longer presentation times (10 s). Understanding is a measure of aesthetic judgment which relies on the evaluation and “cognitive mastery” of an artwork (Leder et al., 2006). These results indicate that additional time is needed to assign meaning to art beyond initial classification and recognition. Because integration is also assumed to take time beyond the initial construction phase, the results are also consistent with the CI framework. However, neither the Millis (2001) nor the Leder et al. (2006) study was meant to test the CI framework directly.

Another reason why the majority of studies in experimental aesthetics do not address the applicability of the CI framework is that in its current form, the CI framework requires input values representing concepts (i.e., anything that might be represented or approximated by a word) and the strength of their connections. In essence, the framework is suited toward meaning. In
contrast, a majority of research in experimental aesthetics have focused on “aesthetics from below,” examining the impact of formal compositional variables (e.g., balance, symmetry), and what are referred to as “collative” variables (e.g., Berlyne, 1974). Collative variables reflect the psychological outcome of comparing elements in a work of art. For example, the collative variable of complexity arises from the judgments of similarity or compatibility between an element and other elements within a pattern (Cupchik, 1992). Novelty, another collative variable, arises from the comparison between a stimulus and previously experienced stimuli. Other collative variables included conflict, surprise and uncertainty. Berlyne (1971) argued that moderate levels of arousal brought about from such variables produce optimal levels of pleasure and have greater impacts than psychophysical variables (e.g., brightness, intensity) and ecological variables (e.g., meaningfulness, associative value).

In order to examine whether the CI framework could be used to account for aesthetic responses, we had to implement it in a way suitable for artworks. The implementation of the framework has varied from one domain to another, and so we will describe a prototypical implementation (Kintsch, 1998). The activation level of N elements activated in a cycle is represented by a N X 1 vector. The elements might represent a concept, a word, or some other unit. In our case, the elements will represent the recognized objects depicted in the artwork. The initial values represent the activation of the elements at time t and typically start with a value of 1. The N X 1 vector is multiplied by a N X N connectivity matrix which represents the strength of relationships among the elements. The values might be positive, negative or zero. The direction and magnitude of these values are typically determined theoretically. For example, if two concepts belong to the same proposition, their connection strength would presumably be
positive representing their mutual facilitation. If two concepts represent two different meanings of a homophone (e.g., money-bank versus river-bank), their connection would presumably be negative, representing their opposing confluence. The N X 1 vector and the connectivity matrix are multiplied resulting in a N X 1 vector containing modified activation values of the original N X 1 vector. The modified N X 1 vector and connection matrix are again multiplied resulting in another set of modified activation levels. If a difference between the respective values in the vectors is greater than some threshold (e.g., .005), then the values of the most recent vector are normalized by dividing each entry by the largest, thus keeping the values within bounds, and it is again multiplied by the connectivity matrix. This process of multiplication and comparing values is repeated until the change is less than the threshold, signifying that the activations have settled.

We made some simplifying assumptions so that we could adapt the CI framework to visual processing. One was that we concentrated on just one level of representation, namely the artbase representation that contains explicitly shown concepts. Although one might be able to include surface information (“Level 1”) and deeper inferences preserved in the situation model (“Level 3”) in the connectivity matrix, we did not do so for the present paper. Another was that we simulated only one construction-integration cycle for all of the concepts in the artwork. That is, all the concepts were assumed to be initially activated before integration occurred. This would be like simulating a multi-clause sentence in one step rather than cycling across clauses. Although viewers do not take in an entire artwork simultaneously, we had no way of knowing the order in which the objects would be apprehended. Lastly, the connectivity matrix contained cosines generated by latent semantic analysis (LSA; Landauer & Dumais, 1997) to represent the semantic similarity among the concepts. Ideally, we would want the connection strengths to
reflect the extent to which each concept is related to one another in the representation of the viewer. We tried to compute a measure of connection strength based on participants’ description of the pictures. This proved this to be unreliable because in several instances, the participants would merely summarize a scene without mentioning many of the concepts that we knew would be activated by virtue of the object distribution. For example, many participants merely wrote “maid on stairs” for the artwork in Figure 1. In addition, the same illustration was described in different ways by different participants, making an assessment of the connection strengths very difficult. In hindsight, these observations are not surprising given that there is a theoretically large number of ways that a single scene can be propositionalized.

Let us now consider an example of how we submitted an artwork to the CI simulation. Consider the painting in Figure 1 that depicts a maid carrying sheets down a staircase. Table 1 lists the objects that are explicitly shown in the artwork (the concepts were collected empirically using a listing task described below). We then submitted the 17 concepts to the Colorado LSA website (HYPERLINK: http://lsa.colorado.edu) which returned a 17 X 17 matrix containing cosines representing the semantic similarity among all of the concepts. This constituted the connectivity matrix for this artwork. (For space reasons, the matrix for the example is not shown in Table 1.) We then multiplied the matrix by a vector containing 17 values, each corresponding to the activation level of the concepts. The activation of each concept was initially set to 1.0. Table 1 shows the activation level for the concepts after each cycle until the change in activation levels was below .005. In this case, it took 5 cycles to settle, and the average activation value of the concepts was .65. In the studies reported in this paper, the measures of interest were the number of concepts, the number of cycles, and the final average activation value of the concepts.
In the studies reported below, we predicted some aesthetic responses to various representational artworks (paintings, water colors, drawings and sketches) from parameters derived from the CI framework. We also included variables accounting for artistic style (i.e., type of brush strokes, use of colors, perspective, balance, etc.). The artistic style variables should reflect to some degree Solso’s “level 1” or surface representation. In contrast, the CI-based variables should be linked to the artbase representation (Solso’s “level 2”) because both focus on the explicitly shown concepts in representational artworks. We do recognize difficulties in conceptualizing the two levels as being entirely independent. On the one hand, two artists might paint the same street scene, and although the two paintings would depict the same objects (e.g., trees, people, etc) there will be differences in style - how they are portrayed (e.g., consider the differences between van Gogh versus Gauguin). In our terminology, the paintings would have the same artbase representation but different surface representations. On the other hand, the style or surface features of the paintings themselves might be different enough to affect the identification of the objects or the salience of their features. Under these circumstances, the surface features would affect the artbase representation. We included variables measuring style so that we could ascertain whether the CI framework would account for aesthetic responses above and beyond what could be attributed to artistic style and the surface representation.

Study 1

For each artwork, we derived values for three parameters based on the CI framework. The first was the number of concepts that would be activated by the explicit artwork. This was our measure of the spread of the network created by the construction process. An artwork that activates few concepts would presumably have a quicker and sparser initial representation than
one that activates several. The second and third CI parameters were the number of cycles that the model took to settle and the final activation values of the concepts once they settled. These two variables are indicators of the integration process. The number of cycles might be an indicator of the time for the viewer to construct a representation, and the final activation values might be an indicator of its coherence.

We had participants supply three measures of their aesthetic response to artworks: ratings of enjoyment, the number of thoughts that occurred as they viewed the artwork, and the extent that they achieved an understanding of the artwork. Of course, there are many types of emotional responses that can potentially arise while viewing art: sadness, wonder, puzzlement, boredom, anger, surprise, etc. Aesthetic responses are highly varied in type and multidimensional (Cupchik & Gebotys, 1990). These three were chosen for two reasons. The first is that aesthetic responses include emotion-based experiences (e.g., pleasure) and cognition-based experiences (e.g., aesthetic judgments, inferences). Enjoyment is a measure of hedonic pleasure which is a common emotional reaction to art (Leder et al., 2004) whereas the number of thoughts and rated understanding might reflect cognition-based experiences. The second reason is that the number of thoughts and understanding has some face validity to the CI framework in that the number of concepts should be correlated with the total amount of initial spread of activation in semantic memory that occurs during the construction phase and understanding should be correlated with the coherence of the resulting representation after integration.

Let us now consider how the CI framework might relate to aesthetic responses. Aesthetic responses might arise from the construction phase, the integration phase, or some combination of the two. If construction gives rise to aesthetic responses, then the number of concepts should be
a significant predictor of the aesthetic ratings. If the integration process results in aesthetic responses, then the number of cycles and final activation values should predict the aesthetic ratings. Because the understanding ratings should reflect the coherence of the integrated representation, the number of cycles and final activation values should also predict the understanding scores.

**Method**

**Participants.** The participants were undergraduate psychology students attending Northern Illinois University who participated as part of a psychology course (Age: $M = 19.2$ years old, $SD = 1.8$). All participants were art novices; no participant had more than two college-level art classes. The average was zero art classes. In addition, the participants scored a mean of 2.1 ($SD = .89$) when asked to specify “how often they viewed art” on a 1 (never) to 6 (very often) Likert-type scale. There was approximately the same number of female and male participants.

There were 150 participants who supplied concept names for each artwork (concept list task) and 179 participants who supplied aesthetic ratings for each artwork (aesthetic rating task). No participant served in both tasks.

**Materials.** There were 110 artworks, consisting of paintings, water-colors, and drawings. Eighty-eight percent of them were in color. All of the artworks were representational; one could readily identify the objects portrayed in art. All of the artworks had been published in art books or magazines devoted to art or graphic design. The topics and themes of the artworks varied. Eleven percent of them had no agent (a person or an animal), 41% had one, 20% had two, and 29% had three or more. Most conveyed conventional scenes, like an illustration of a woman gardening, but for others, the scenes were more unique, like an illustration of a person diving into
a pool filled with newspapers. We tried to sample artworks haphazardly with the constraint that a person could identify the objects portrayed in them. Furthermore, none of the artworks were known or familiar to our participants, as ascertained by a post-experiment questionnaire.

Coding artworks on the surface representation. We considered two possible methods for quantifying surface representations. The first was to rate each artwork on variables relevant to the surface representations, such as color, complexity, balance, etc. This procedure has been used on simple stylized materials (e.g., Berlyine, 1974). However, it was not obvious which dimensions and scaling procedures to use for more complicated and authentic materials. For example, one might be able rate an artwork on the number and intensity of hues, but dispersion throughout the artwork is much harder to quantify. The second option, which we adopted, was to group the artworks according to artistic style based upon holistic impressions. Each artwork was printed on a small card. Two raters (the two authors), working together, placed cards whose artworks shared stylistic similarities on top of each other. The guiding principle was whether the artworks in a pile looked as though they were created by the same artist. All of the artworks in a group shared similar surface characteristics, such as color, the length and width of brush strokes, rhythm, and medium (e.g., water-color, oil). We went through the stack of all artworks once, forming piles, and after this was done, we went through all of them again to verify the sorting. In all, we identified 13 different styles. The mean number of artworks in a group was 11 (SD = 7).

Coding artworks on CI parameters. We identified the concepts that each artwork would normally activate for the average individual by asking participants in a “concept list task” to write down all of the objects (e.g., things, places, people) that they explicitly noticed in each artwork. Each participant saw approximately 33 artworks, and each artwork was rated by
approximately 20 participants. For each artwork, we computed a distribution of all of the objects mentioned by 2 or more participants. We collapsed over synonymous words that referred to the same object in the artwork and gave credit to the most frequent word. For example, if 10 listed “girl” and 3 listed “woman” and 2 listed “lady,” then we collapsed these as 15 responses for “girl.” We recognize that this may not be optimal because the different words could lead to different simulated parameter values. For example, ‘girl’ and ‘lady’ have different senses and semantic representations. Most of the time only one word was selected to represent a single element in the artwork. However, there were instances when we included two terms to denote the same element. This arose when the words were sufficiently semantically different from each other as judged by the first author. For example, the words ‘maid’ and ‘woman’ were used by 8 and 2 participants to describe the person in Figure 1. Presumably, some viewers interpreted the person as a ‘maid’ and some as the more generic and superordinate ‘woman’. Instead of choosing one, we included both.

We constructed a connectivity matrix for each artwork. As mentioned earlier, the connectivity matrices in this study represented the semantic similarity among the concepts. We used latent semantic analysis (LSA) to estimate the semantic association among the concepts (Landauer & Dumais, 1997). LSA is a statistically-based method which represents the association among two units of language (words, phrases, texts). It does so by computing a cosine between two vectors of a matrix that contains words on one side and dimensions on the other. The dimensions are derived from applying a principal component analysis on a matrix representing co-occurrences within a large corpus of text. The magnitude of the cosine represents their semantic similarity. For example, the cosine between the words “planet” and
“sun” is .47 whereas the cosine between “planet” and “chair” is .02. We used LSA values obtained by the University of Colorado website using the general reading data-base.

Using the concepts gleaned from the listing task and the LSA values, we computed the following parameters for each artwork: number of concepts, number of cycles, and average final activation. We used the algorithm described in the introduction with the connectivity matrix containing LSA cosines. The number of concepts was simply the number of concepts associated with each artwork (as determined by the listing task). The number of cycles was the number of cycles for the CI algorithm to settle with a criterion change value of .005. The average final activation was the average final activation for the concepts once settling occurred. The descriptive statistics for these are shown in Table 2.

Procedure

Collecting ratings of aesthetic responses. The artworks were randomly assigned to 6 stimulus lists. We included a number of photographs across the lists, but these were not analyzed because they were not of interest to the present studies. Overall, the number of artworks (illustrations and photographs) in the six lists ranged from 31 to 36. Participants were randomly assigned to a stimulus list when they arrived at the study. Participants were tested individually in small rooms, sitting in front of a computer monitor. They were instructed that they would be viewing artworks on the computer screen and that they would be answering questions about their viewing experiences. They were instructed to view the artworks for as long as they wished. The artworks were presented one at a time in a randomized order for each participant. When participants pressed the space bar, an artwork appeared on the screen. When they finished viewing the artwork, they pressed the space bar again, and the artwork was replaced by three
questions, which were also presented one at a time. The first question asked participants to rate their “enjoyment” of viewing the artwork using a Likert-type scale (1 = not at all, 6 = extremely enjoyable). The second question asked how many thoughts, ideas, or memories they experienced as they viewed the artwork (1 = none, 6 = several). The third question asked them the extent that they created a coherent understanding of the artwork (1 = not at all, 6 = very much). Participants went through this cycle of viewing and then answering questions about an artwork until they had viewed and rated all artworks in their stimulus list. Participants rated three practice artworks to get them acquainted with the procedure. The computer recorded all ratings and the time spent viewing each artwork.

Results and Discussion

For each artwork, the mean rating for enjoyment, number of thoughts, and understanding was computed (see Table 2). These scores served as the dependent variables in the regression analyses reported below. The means centered around or above the midpoint of the scale, indicating moderate levels of each. The correlations among the scores ranged from .58 to .73. The .73 correlation occurred between enjoyment and understanding, indicating that participants enjoyed what they understood. The descriptive statistics for the predictor variables are also shown in Table 2. The following correlations were obtained for the CI predictor variables: number of concepts and the number of cycles, \( r = -.45 \); number of concepts and activation, \( r = -.54 \); number of cycles and activation, \( r = -.09 \). The pattern of correlations indicated that artworks with more concepts resulted in fewer cycles and lower final activation values. The bivariate correlations among the dummy-coded variables assessing the surface representation ranged from -.29 to .21. The magnitude of the correlations suggests that collinearity should not impose
interpretational problems of the regression coefficients.

We wanted to estimate the unique variance of the ratings associated with the surface representation and the artbased representation as reflected by the CI variables. In order to do so, we entered the predictor variables in two steps. To assess the unique contribution of the surface representation, we first entered the CI predictors in step 1, followed by the group of dummy-coded variables assessing artistic style in step 2. The change in $R^2$ associated with step 2 would indicate the amount of variance in the DV accounted by the surface representation above and beyond the impact of the CI variables. Similarly, the impact of the CI variables was assessed by the change in $R^2$ when they were entered after the variables accounting for the surface representation were entered in another regression equation. We report the resulting standardized regression coefficients (beta weights) and changes in $R^2$ when they were entered in the second step since this would represent their impact above and beyond the other group of predictors.

The results are presented in Table 3. For each of the three ratings, enjoyment, thoughts, and understanding, the regression equations were significant, accounting for approximately 29% of the variance. The CI variables assessing the artbase representation accounted for statistically significant amount of the variance in each of the ratings. The $R^2$s ranged from .07 to .10, $p$’s < .001. In regard to the individual CI predictors, the number of concepts was statistically significant for all ratings, with beta weights ranging from .37 to .52. The positive values of the weights indicate that the aesthetic responses increased with more concepts. The final activation value of the concepts predicted enjoyment and understanding ratings but not the number of reported thoughts. The positive value of the significant weights, which ranged from .28 to .33, indicated a preference for artworks which had higher final activation values. Lastly, the number
of cycles predicted enjoyment but not the number of thoughts nor the understanding ratings. Presumably, participants enjoyed artworks which took more cycles to settle according to CI.

We also predicted the viewing time of the artworks. Because the viewing times were significantly positively skewed, we transformed them using a logarithmic transformation. The overall equations were significant ($R^2$s = .25, $p < .05$). Interestingly, the surface representation variables accounted for all of the variance. This finding suggests that artistic style and the surface representation affected the viewing time but not the resulting aesthetic response. This is consistent with a model of aesthetic responses proposed by Leder et al. (2004) that assumes emotional experiences are immediately available as the artwork is processed, but aesthetic judgments and evaluations of the artwork result from a set of serially-ordered processes that require time to perform.

The number of activated concepts predicted enjoyment, number of thoughts, and understanding. Because the number of concepts represented the construction phase of CI, it supports the claim that aesthetic responses arise from the initial activation of concepts. (We should point out that perhaps it is not too surprising that the number of concepts predicted the number of thoughts because each concept could trigger a thought.) The final activation level predicted enjoyment and understanding but not the number of thoughts. This variable represented the integration phase when activated concepts settle into a stable network. This suggests that at least some of the aesthetic responses are tied to the integration process. Together these results provide initial support for the claim that aesthetic responses arise from a construction-integration process.

Study 2
In this study, we attempted to separate the effect of the construction and integration processes by manipulating viewing time. Participants either viewed the artworks for a relatively brief amount of time (3 secs) or for a relatively long time (17 secs) before supplying the aesthetic ratings. Assuming that construction takes a relatively brief amount of time, the participants in the short viewing time condition would be answering the questions during or briefly after the construction process. (This assumes that participants cannot speed up the construction processes because of the speeded viewing times.) On the other hand, participants in the long viewing time condition would be answering the questions after the completion of both construction and integration processes.

Finding dissociation between construction and integrative processes would provide further evidence supporting the CI framework in this domain. Dissociation would occur if the variables assessing construction would be more significant in the short viewing condition than in the long viewing condition, and the variables assessing integration would be more predictive in the long viewing condition than in the short viewing condition. Therefore, if the number of concepts is indeed related to construction, and if construction is related to aesthetic responses, then this variable should be more predictive in the short than in the long viewing time condition. Similarly, if the final activation value is more linked to integration than to construction, as it ought to be, then this variable should be more predictive in the long viewing time condition than in the short viewing time condition.

Method

Participants. There were a total of 266 undergraduate psychology students attending Northern Illinois University who participated for course credit.
Procedure

The procedure was identical to Experiment 1 except that participants were randomly placed into either the short ($N = 134$) or long viewing time condition ($N = 132$) upon arrival to the laboratory. They were then randomly assigned to one of the six stimulus lists. The artworks were shown on the computer monitor for a fixed amount of time in both viewing conditions: 3 seconds for the short group and 17 seconds for the long group. These durations were chosen because they represented roughly 3 standard deviations above and below the mean obtained by the unrestricted viewing times from Study 1. Participants in both groups were instructed to view each artwork for as long as they remained on the screen. Participants in the long group were additionally told that if they should keep viewing the artwork even if they felt bored or that it was time to progress to the next artwork. Participants answered the three questions after each artwork was removed from the screen.

Results and Discussion

To understand the overall effect that viewing time had on the aesthetic ratings, we submitted each aesthetic rating to a paired t-test with viewing time as the independent variable. The unit of analysis was the artwork. All statistical assumptions were met. The mean enjoyment rating for the short and long viewing time conditions were 3.27 ($SD = .51$) and 3.29 ($SD = .54$), respectively. As one can see, viewing time had virtually no impact on the enjoyment ratings, $t(109) = .50, p < .75$. However, participants reported significantly more thoughts ($M = 3.89, SD = .53$) in the long viewing condition than in the short viewing condition ($M = 3.78, SD = .55$), $t(109) = 2.57, p < .05$. Additionally, participants reported greater understanding in the long viewing time condition ($M = 3.56, SD = .68$) than in the short viewing time condition ($M = 3.41,$
$SD = .67$, $t (109) = 3.69, p < .01$. These results suggest that the extra viewing time enabled the participants to have more thoughts regarding the artwork and allowed them time to gain an optimum level of understanding. This is consistent with the assumption that integrative processes would have been completed in the long viewing time condition.

The regression equations were computed in the same manner as in Experiment 1. The results are presented in Table 4. As a group, the CI predictors were significant in the short but not in the long viewing time condition. The $R^2$'s were comparable to Study 1, ranging from .07 to .12 ($p$’s < .05). As predicted, the number of concepts was a significant predictor when the artworks were viewed relatively quickly but not when the artwork was viewed for a relatively long time. The number of concepts should be related to the construction phase when an initial representation is constructed from a quick and bottom-up spread of activation. Therefore, the pattern of significance for the number of concepts indicates that when processing is interrupted near the time when construction is completed, the aesthetic experience is positively correlated with the divergence of the spread.

The final activation level was significant at both short and long viewing times. Presumably, the final activation level represents the representation after the integration phase. We expected this predictor to be more significant in the long viewing time condition, when integration would be expected to be complete. The fact that it was significant at both times suggests that integration occurred very quickly, so that integration was completed (at least for many of the artworks and participants) by the time participants in the short viewing time condition answered the questions. This certainly seems plausible given that pattern recognition is automatic, leading to very quick concept activations and that some aspects of aesthetic
judgments are available within 500 ms (Ognjenovic, 1991).

Study 3

There are many types of aesthetic responses to artwork that might be related to the CI framework. As mentioned earlier, the measures of enjoyment, number of thoughts and understanding generally fit into a demarcation between emotional and cognitive aesthetic responses (Cupchick, 1992; Leder et al., 2004; Russell & Milne, 1997). Aesthetic emotions refer to affective states like pleasure or satisfaction, whereas cognitive responses refer to aesthetic judgments regarding the artwork (Leder et al., 2004). A person might experience pleasure while looking at a painting but yet judge its composition to be a poor example of a particular style. Alternatively, a viewer might judge the aesthetic value of a painting to be quite high yet feel little emotion.

In regard to this emotion/cognition contrast, enjoyment ratings likely reflect emotional responses to a greater extent than cognitive responses, whereas the opposite is probably true of the number of thoughts and understanding ratings. We should note that negative emotions such as displeasure, anger or sadness may also arise, but they tend to be less common than positive emotions (Leder et al., 2004) and less common for art novices as compared to experts (Cupchik & Gebotys, 1990). The finding that the CI variables predicted enjoyment ratings in both Studies 1 and 2 but only the number of thoughts in Study 1 raises the question of whether the model is a better predictor of emotional than cognitive experiences. The fact that understanding ratings were equally predictive in both studies suggest that the model is predictive of cognitive responses, but the high correlation between enjoyment and understanding ratings ($r = .73$) calls into question of whether the understanding scores were capturing emotional or cognitive
experiences, or some combination of both.

The goal of Study 3 was to directly test whether the CI predictors are more or equally predictive of cognitive and emotional aesthetic responses. In this study, we had participants rate each artwork on measures that should be related to the cognitive and emotional dimensions. Based on existing research in experimental aesthetics (e.g., Berlyne, 1974; Cupchik & Geoty, 1990; Graesser et al., 1996; Hekkert & van Wieringen, 1996; Russell & Milne, 1997), we chose meaningfulness, complexity, and interestingness ratings to represent cognitive-based responses, and liking and pleasingness ratings to represent emotion-based responses. We then used principal components analysis to confirm these two components and generate factor scores for each artwork. We then predicted the factor scores from the CI and surface representation variables to assess their unique contribution to both types of aesthetic responses.

*Method*

*Participants.* One-hundred twenty six undergraduate psychology students attending Northern Illinois University participated for course credit.

*Procedure.* The procedure was identical to the one used in Study 1. Participants were randomly assigned to one of the 6 stimulus lists. The participants first viewed each artwork on a computer screen as long as they wished before rating it on the measures. First, they were asked to rate it on pleasingness – the extent they found the artwork to be pleasing and pleasurable to view (1 = not pleasing, 6 = very pleasing). Second, they rated it on meaningfulness which was defined as the extent that the artwork conveyed ideas and meaning to them (1 = not at all meaningful, 6 = very meaningful). Third, they rated their interest of the artwork (1 = uninteresting, 6 = very interesting). Fourth, they rated how much they liked viewing the artwork
(1 = dislike, 6 = like very much). Fifth, the participants were asked to rate the complexity of the artwork (1 = very simple, 6 = very complex).

Results and Discussion

The mean of each rating was computed for each artwork. The means (and standard deviations) for pleasingness, meaningfulness, interest, liking, and complexity were 3.21 (.56), 3.48 (.67), 3.94 (.57), 3.42 (.50), and 3.71 (.57), respectively. The bivariate correlations ranged from .07 to .71. The mean ratings for each artwork \((N = 110)\) were submitted to a principal components analysis using a varimax oblique rotation. The analysis revealed two principal components with Eigenvalues greater than 1.0. The first and second components accounted for 45\% and 40\% of variance, respectively, with a cumulative percentage of 85. The rotated component matrix is presented in Table 5. The entries in the matrix reflect the unique relationship between each measure and component. As expected, the measures of complexity, interest, and meaningfulness loaded much more heavily on the same component (component 1) whereas liking and pleasingness loaded heavier on the other (component 2). The number of factors, along with the pattern of loadings indicated components 1 and 2 reflected cognitive- and emotional-based aesthetic responses, respectively.

Based on the principal component analysis, factor scores were generated on each of the two components for each artwork. The factor scores represent estimated scores on the two components (factors). Therefore, for each artwork, we had scores representing the degree that it had elicited cognitive- and emotional-based aesthetic responses for our sample of participants. We predicted these scores from the CI and the surface representation variables in the same manner as in the previous studies. Overall, the variables predicted a significant amount of
variance in the emotion and cognitive scores (both $R^2$'s = .25, $p$'s < .05). In regard to emotion, the CI predictors accounted for a significant amount of unique variance ($R^2 = .10, p < .01$). Each of the CI variables (number of concepts, number of cycles, average activation) was statistically significant ($p$'s < .05). The beta weights were .49, .28, and .36, respectively. However, the style variables failed to reach statistical significance despite the finding they also accounted for same amount of unique variance ($R^2 = .10, p < .50$). This undoubtedly occurred due to the greater number of degrees of freedom associated with the set of style predictors. Nevertheless, the style predictors accounted for a significant amount of unique variance of the cognitive scores ($R^2 = .22, p < .05$). In contrast, the CI predictors failed to predict a significant amount of unique variance of the cognitive scores ($R^2 = .02, p < .60$).

The results indicate that the CI framework accounted for the emotion- but not cognitive-based aesthetic responses. Specifically, the variables liking and pleasingness are indicators of hedonic pleasure, the extent that we experience positive emotions as we view artwork. On the other hand, the style predictors assessing the surface representation accounted for much more of the cognitive-based experiences. This finding suggests that differences in artistic style account for aesthetic judgments on meaningfulness, complexity, and interest.

One question that arises is whether the ratings used in the previous studies were closer to the emotion- or cognitive-based experiences. To answer this question, we correlated these ratings with the factor scores. Both understanding and enjoyment scores were highly correlated with the emotion factor scores ($r$'s = .66, .82, $p$’s < .001) but not with the cognitive scores ($r$’s = .05, .10, $p$’s < .60), indicating that the understanding scale is closely tied to pleasure and not to cognitively-based judgments. The number of thoughts was equally correlated with the emotion
and cognitive factor scores ($r$’s = .45, .56, respectively, $p$’s < .001).

General Discussion

The current studies indicate that some aesthetic responses to artwork can be understood within the construction-integration framework. According to the framework, the concepts that are explicitly shown in the artwork are initially activated within working memory, probably along with their close semantic associates. During this construction phase, the viewer experiences aesthetic responses consisting of hedonic pleasure (enjoyment, pleasingness) and a perceived sense of understanding. The magnitudes of these responses depend on the richness of the spread. The richer the spread, as measured here by the number of activated concepts, the greater the response. However, the aesthetic emotion linked to this construction process appears to dissipate by 30 seconds. Presumably during this time, the viewer is integrating the activated concepts into a more coherent representation, heightening the activation of some concepts and deactivating others. The more the concepts remain active, the more hedonic pleasure the viewer experiences. The pleasure associated with the integrated representation also lasts for at least 30 seconds (and possibly longer).

Because the input values to the model were based on activated concepts depicted in the artwork along with their estimated associations in long-term memory, it might be seen as somewhat counter-intuitive that the CI framework accounted for emotional experiences and not cognitively-based ones. One reason for this finding may be that art novices tend to process artworks on content (Winston & Cupchik, 1992), and because our participants were art novices, it seems reasonable that a model or framework that focuses on content was able to account for at least some of their emotional responses. It is unknown whether the CI framework as it was
implemented here would account for aesthetic responses held by art experts since they emphasize composition and style (e.g., cognitively-based aesthetic judgments) over content (Cupchik, 1992; Cupchik & Gebotys, 1988). It is also unknown whether the CI framework could be adapted to other types of artwork, such as abstract art, sculpture, performance art, etc.

As it stands now, the CI framework partially accounts for aesthetic responses that arise from the activation of concepts depicted in a representational artwork. Of course, the semantic features of the artwork only contribute to only part of the aesthetic experience. Surface characteristics and style was omitted from the CI implementation, not to mention other important factors (e.g., the characteristics of the viewer, context, etc.). One might extend the CI framework to account for surface characteristics (e.g., color, shading, perspective, composition, style) by modifying the connectivity matrices in a similar way that researchers have included syntactic and lexical information in CI simulations of text (e.g., Singer & Halldorson, 1996).

The CI framework might also be extended to account for aesthetic responses to verbal discourse. For example, the approach taken here could be applied to poetry, although how successful it would be is unknown. Again, the CI framework might be adopted to account for the surface features of poetry, the rhythms, cadence and phonological attributes. One important aspect of poetry, and more generally of any verbal input, is that the meaning of a word depends on context. For example, the semantic representation of “Lilacs out the dead land, mixing” (T.S. Elliot’s *The Wasteland*) is probably not a summation of the semantic representations of its individual words. Rather meaning emerges dynamically out of the full context. At minimum, context affects which semantic senses of a word are heightened and which are deactivated. Kintsch (2001) introduced the predication model which uses LSA and the CI framework to
produce contextually appropriate senses of a predicate in simple argument-predicate sentences.

The CI framework is used to select words in the semantic neighborhood of the predicate that are in some way related to the argument, and then the selected words are used to modify the semantic vector of the predicate. For example, Kintsch (2000; Kintsch & Bowles, 2002) has used the predication model to simulate the meaning of metaphors. Kintsch and Bowles (2002) found the semantic representations of metaphors produced by predication had a good fit with participants’ understanding of metaphors as assessed by a sentence completion task that required the participant to give a literal interpretation of the metaphor (e.g., “My lawyer is ________ [e.g., aggressive]” after reading “My lawyer is a shark”). One might speculate that something like the predication model could help account for emotional responses to poetry (and perhaps to artwork) because emotions are often expressed by metaphor (Gibbs & Nascimento, 1996).

Interestingly, the CI framework shares some broad architectural similarities with Berlyne’s psychobiological theory of aesthetic processing (Berlyne, 1971; also see Berlyne, 1974). A central aspect of that model is that preference is determined by the arousal potential brought about from the intrinsic physical properties of the artwork (e.g., brightness, saturation), innate or learned meaningfulness, and the amalgamation of two or more variables associated with the stimulus and/or the viewer, such as complexity, novelty, or surprise (i.e., the collative variables mentioned in the Introduction). Berlyne emphasized the role of collative variables on arousal potential. The pleasure and pain centers in the midbrain are activated as the visual information passes to the cortex. Because the pleasure centers have a lower threshold than the pain centers, initial arousal leads to increased preference which ultimately reaches an asymptote. However, as the arousal increases, the pain centers are then activated which decreases preference.
and which also reaches an asymptotic level. We experience the summation of both curves which is an inverted U-shape when plotted against preference, a function that Berlyne (1971, p. 89) attributes to Wundt. Intuitively, we are bored by white wallpaper, preferring some patterns, but we will dislike it if it is too “busy.”

The similarity between the CI framework and the psychobiological model is worth noting. There is a rise and fall of activity in both. The rise and fall is physiological in the psychobiological model (i.e., the Wundt curve) whereas it is semantic in the CI framework. Both rise and fall are governed by different underlying processes. In the psychobiological model, they are the pleasure and pain centers in the midbrain, whereas in the CI framework, they are the spread of initial activation and the connectionist settling process. One consequence of Berlyne’s model is that there are two ways to increase preference or pleasure. One is to increase or boost arousal when it is low, and other is to decrease arousal when it is high. An “arousal jag” occurs when a person seeks increased arousal for the pleasurable relief that occurs when it is decreased (Berlyne, 1971, p. 136). Because art is experienced across time, arousal jags probably occur as the tension brought about from arousal-increasing variables (psychophysical, ecological, collative) are encoded and run their course toward certainty. It might be possible for the CI framework to account for the semantic analog of arousal jags if eye movements were recorded and temporality was accounted for by the simulation. That is, one could simulate the increase and decrease of activation as each new element is encoded across time. This type of arousal-mediation or “rise and fall” architecture is fairly common in experimental aesthetics (Kreitler & Kreitler, 1972). Berlyne (1974) cites several other researchers who describe aesthetic response “on the interplay of two sets of factors, one tending to drive arousal upwards and the other
tending to reduce arousal or to keep it within bounds” (p. 9).

Berlyne also distinguishes between diversive and specific modes of exploratory behavior. Diversive behavior occurs when the viewer seeks out stimulation by inspecting the stimulus with widely dispersed eye fixations (Nodine, Locher, & Krupinski, 1993). Diversive behaviors primarily occur during initial viewing (Locher & Nodine, 1987). Specific behavior occurs when the viewer focuses on content, drawn in by some curiosity or by some other incomplete perception, and is expressed by short gazes on particular areas of the stimulus. It is intuitively appealing to link Kintsch’s construction process with positive arousal and diversive behavior, since both denote a “rise” of the cognitive system, one of uncertainty and ambiguity. Similarly, one might link integration with negative arousal and specific behavior because they both suggest a “fall” of the cognitive system or a direction toward coherence and familiarity.

Besides the general “rise” and “fall” associated with construction and integration, one feature that appears to be important for accounting for aesthetic responses is the pattern of semantic associations among the depicted objects. This was clearly demonstrated to us when we attempted to predict aesthetic ratings from final activation levels computed from connectivity matrices containing randomly selected cosines. These matrices were similar to the original ones in all other respects. However, these activation levels never predicted the aesthetic ratings in any viewing condition. We should also note that the mean value of the cosines in the original connectivity matrices never predicted the aesthetic responses. One possible explanation for why the pattern of cosines in the connectivity matrices and the integrative process are important is that they encode or otherwise reflect the coherence, familiarity or prototypicality of the scene depicted in the artwork. Familiarity and coherence are important to consider because art novices focus on
familiar content, preferring relatively simple representational artwork that resemble the world around them (Schmidt, McLaughlin & Leighten, 1989). In contrast, art experts prefer more complicated and less representational artworks (Cupchik & Geotys, 1988). Therefore, it is possible that the final activation scores predicted the emotion-based scores because they were correlated with familiarity or the visual coherence of the illustrations.

The CI framework is also consistent with more recent models of aesthetics which emphasize ecological variables (e.g., meaning, semantic content, associations). For example, Martindale (1984) proposed a connectionist model that represents semantic elements and their prototypicality. Martindale, Moore, and West (1988) has showed that preference for members of a category (e.g., birds, tools) was better explained by their typicality of that category than word frequency and repeated exposures, both measures of the collative variable of novelty (also see Hekkert & Wieringen, 1990). The CI framework is also consistent with a model proposed by Leder et al. (2004) which assumes positive and negative aesthetic emotions accumulate from a set of serially-ordered processes: perceptual analyses (symmetry, grouping), implicit memory integration (familiarity, prototypicality), explicit classification (artistic style), cognitive mastering and evaluation (interpretation, reaching a satisfactory understanding). Although Leder et al. (2004) did not postulate specific implementations of any of the stages, the CI framework might be useful for implementing the memory integration stage, where familiarity and prototypicality is associated with affective preference.

In summary, the CI framework is broad enough to account for some aesthetic responses to artwork. In this regard, aesthetic responses to art can be added to the list of domains mentioned at the beginning of this paper to which the CI framework has been successfully applied. Because
visual art is a type of discourse, the findings might be relevant to new and old questions related to the study of traditional discourse. Could the CI framework provide a metric of aesthetic response to literary text? To what extent do emotions arising from structural aspects of discourse (e.g., an unexpected event) are dependent on or modified by emotions which arise from individual words? What is the function of aesthetic responses to the interpretation, encoding, and memory for literary and other types of text? Obviously, future research is needed to answer these and other questions.
Author Note

The authors would like to thank Katie Schafer, Julie Bonini and Brian Salmon for help with data collection. Correspondence regarding this manuscript and requests for reprints should be directed to Keith Millis, Department of Psychology, Northern Illinois University, Dekalb, IL 60115 (USA) or to kmillis@niu.edu.
Footnotes

1 Some researchers have pointed out that the relation between arousal potential and preference is ambiguous and the assumption that requires two stimuli to be equally preferred given equal arousal potentials to be dubious (Martindale, 1984).
References


Psychological Review, 4, 211-240.


Table 1. Computing CI measures for the artwork in Figure 1. Entry numbers are the activation levels of each concept across cycles.

The summary variables were predictor variables used in the regression equations.

<table>
<thead>
<tr>
<th>Cycle</th>
<th>maid</th>
<th>woman</th>
<th>carrying</th>
<th>sheets</th>
<th>staircase</th>
<th>picture</th>
<th>wall</th>
<th>man</th>
<th>towels</th>
<th>holding</th>
<th>dark</th>
<th>walking</th>
<th>down</th>
<th>stairs</th>
<th>winding</th>
<th>watching</th>
<th>blankets</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.63</td>
<td>.58</td>
<td>.77</td>
<td>.48</td>
<td>.69</td>
<td>.36</td>
<td>.62</td>
<td>.59</td>
<td>.52</td>
<td>.79</td>
<td>.79</td>
<td>.77</td>
<td>1</td>
<td>.83</td>
<td>.58</td>
<td>.78</td>
<td>.65</td>
</tr>
<tr>
<td>2</td>
<td>.59</td>
<td>.54</td>
<td>.75</td>
<td>.42</td>
<td>.67</td>
<td>.30</td>
<td>.58</td>
<td>.56</td>
<td>.47</td>
<td>.79</td>
<td>.78</td>
<td>.78</td>
<td>1</td>
<td>.83</td>
<td>.54</td>
<td>.78</td>
<td>.61</td>
</tr>
<tr>
<td>3</td>
<td>.58</td>
<td>.52</td>
<td>.74</td>
<td>.40</td>
<td>.67</td>
<td>.28</td>
<td>.57</td>
<td>.55</td>
<td>.45</td>
<td>.79</td>
<td>.77</td>
<td>.78</td>
<td>1</td>
<td>.81</td>
<td>.53</td>
<td>.78</td>
<td>.60</td>
</tr>
<tr>
<td>4</td>
<td>.57</td>
<td>.52</td>
<td>.74</td>
<td>.39</td>
<td>.67</td>
<td>.27</td>
<td>.57</td>
<td>.55</td>
<td>.44</td>
<td>.79</td>
<td>.77</td>
<td>.78</td>
<td>1</td>
<td>.81</td>
<td>.53</td>
<td>.79</td>
<td>.60</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---No change---

Summary: 17 objects, 5 cycles to settle, average final activation is .63.
Table 2. Descriptive statistics for the aesthetic ratings (Study 1) and the CI predictors.

<table>
<thead>
<tr>
<th>CI Predictors</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of concepts</td>
<td>8.7</td>
<td>(3.8)</td>
</tr>
<tr>
<td>Number of cycles</td>
<td>9.0</td>
<td>(3.0)</td>
</tr>
<tr>
<td>Average final activation</td>
<td>.71</td>
<td>(.08)</td>
</tr>
</tbody>
</table>

Aesthetic Ratings

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enjoyment</td>
<td>3.5</td>
<td>(.56)</td>
</tr>
<tr>
<td>Thoughts</td>
<td>3.9</td>
<td>(.56)</td>
</tr>
<tr>
<td>Understanding</td>
<td>3.7</td>
<td>(.73)</td>
</tr>
</tbody>
</table>

Viewing Time (in secs) 13 (3.5)
Table 3. Unique variance ($\Delta R^2$) associated with the surface representation and the CI predictors (and beta weights for the CI predictors).

<table>
<thead>
<tr>
<th>Aesthetic Ratings</th>
<th>Enjoy</th>
<th>Thoughts</th>
<th>Understand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Surface ($\Delta R^2$)</td>
<td>.13</td>
<td>.16</td>
<td>.15</td>
</tr>
<tr>
<td>CI ($\Delta R^2$)</td>
<td>.10**</td>
<td>.07**</td>
<td>.07**</td>
</tr>
<tr>
<td>Equation $R^2$</td>
<td>.29**</td>
<td>.28**</td>
<td>.28**</td>
</tr>
</tbody>
</table>

CI variables (beta weights)

| Concepts | .52*   | .37**  | .37**  |
| Cycles   | .25*   | .05    | .12    |
| Activation | .33** | .14    | .28**  |

Note: * $p < .05$; ** $p < .01$
Table 4. Unique variance (changes in $R^2$) associated with the surface representation and the CI predictors as a function of viewing time (study 2).

<table>
<thead>
<tr>
<th>Representation</th>
<th>Short Viewing Time</th>
<th>Long Viewing Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Enjoy</td>
<td>Thoughts</td>
</tr>
<tr>
<td>Surface ($\Delta R^2$)</td>
<td>.13</td>
<td>.21**</td>
</tr>
<tr>
<td>CI ($\Delta R^2$)</td>
<td>.07*</td>
<td>.12**</td>
</tr>
<tr>
<td>Equation $R^2$</td>
<td>.22</td>
<td>.35**</td>
</tr>
</tbody>
</table>

CI variables (beta weights)

<table>
<thead>
<tr>
<th></th>
<th>Short Viewing Time</th>
<th>Long Viewing Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Enjoy</td>
<td>Thoughts</td>
</tr>
<tr>
<td>Concepts</td>
<td>.38**</td>
<td>.52**</td>
</tr>
<tr>
<td>Cycles</td>
<td>.12</td>
<td>.14</td>
</tr>
<tr>
<td>Activation</td>
<td>.33**</td>
<td>.22</td>
</tr>
</tbody>
</table>

Note: * $p < .05$; ** $p < .01$
Table 5. Component loadings from principal component analysis (Study 3).

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pleasingness</td>
<td>.23</td>
<td>.88</td>
</tr>
<tr>
<td>Enjoyment</td>
<td>.10</td>
<td>.92</td>
</tr>
<tr>
<td>Complexity</td>
<td>.94</td>
<td>-.07</td>
</tr>
<tr>
<td>Interest</td>
<td>.83</td>
<td>.42</td>
</tr>
<tr>
<td>Meaningfulness</td>
<td>.78</td>
<td>.43</td>
</tr>
</tbody>
</table>
Figure Caption Page

Figure 1. An example artwork.